11. Uncertainty Analyses

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The goal of an uncertainty analysis is to determine the model parameters that contribute the most variability to the performance measures. The uncertainty analysis reported here examines the following performance measures:

An uncertainty analysis attempts to determine the model parameters that contribute the most variability to the performance measures.

- Radiation dose at two different locations to an adult individual under a residential farming scenario utilizing groundwater for irrigation of crops:
    - East of the 200 East Area, near the centerline of the groundwater plume moving east toward the Columbia River.
    - North of Gable Gap, near the centerline of the groundwater plume moving north from the 200 West Area and part of the northern portion of the 200 East Area.
- Size of the land area where one or more contaminants in the underlying groundwater exceed their respective levels for the drinking water standard.
- Concentration of tritium in Columbia River water at the Richland municipal water intake.
- Radiation dose and chemical exposures for species living along the Columbia River.
- Total employment in the regional economic model as affected by these contaminants on the environment.

The System Assessment Capability (SAC) was designed and developed as an uncertainty analysis capability because the Washington State Department of Ecology, Tribal Nations, and stakeholder community indicated a desire to quantify the uncertainty in risk and impact metrics. Further, in Department of Energy (DOE) Order 435.1, DOE indicated a desire to see uncertainty and sensitivity analyses of sitewide and waste specific performance.

This analysis addresses the role of uncertainty as caused by the variation of parameters within the modeling system. It does not address causes of errors between the modeled and observed data, those have been discussed in previous chapters. It does not address uncertainty due to the use of different models. In addition, the analysis presented here does not differentiate between uncertainty due to lack of knowledge and uncertainty due to natural variability in the parameters. However, examination of the key uncertain parameters can often determine whether the statistical distribution for the parameter is based mostly on knowledge uncertainty or inherent parameter variability. A two-stage Monte Carlo analysis that would allow separation of these two types of uncertainty was not performed as part of this analysis.

The uncertainty analysis identifies controlling sources of variability in the simulation estimates of the performance measure, but not necessarily the source of the overall magnitude of the performance measure. However, the source of the overall magnitude can be obtained from direct examination of the model results.

Uncertainty Analysis Techniques

The SAC model used a set of 25 output results and 25 values for each uncertainty parameter as a starting point for the uncertainty analysis.

Numerous input parameters are required for the suite of inventory, release, transport, and risk/impact models. Statistical distributions were assigned to many of these parameters, and 25-realization model runs were performed. These input statistical distributions were assigned through a variety of methods including application of field data, utilization of expert opinion, and, for some parameters, assignment of a somewhat arbitrary level of variability due to lack of data. In some cases, the uncertain input parameters describe the behavior and activities of an individual rather than the physical parameters in a waste form release or transport model.

The set of 25 output results, along with the suite of 25 values for each uncertain parameter, served as the starting point for the uncertainty analysis. A step-wise linear regression analysis was performed using the output results and input parameters. The modeling sequence from inventory to impact result is very complex, and in many instances, the inputs to a given model or equation are themselves the outputs of earlier models or equations. Thus, to locate the most influential parameters in the uncertainty of final impact estimates, a top-down hierarchical analysis was performed. This approach is similar to that used for the Hanford Environmental Dose Reconstruction Project (Farris at al. 1994). In this approach, the first tier of analysis considered the major contributing inputs to the performance measure being evaluated. Sometimes the inputs to the specific impact model were derived values, such as the concentration of tritium in groundwater, rather than values of a sampled parameter. If the uncertainty in the performance measure was sensitive to one or more of the derived (previously modeled) parameters going into the equation, then the uncertainty analysis proceeded to the second tier and examined the uncertainty in the derived parameters.

What is a Monte Carlo analysis? *A Monte Carlo analysis is a problem-solving technique that uses statistical methods to solve mathematical or physical problems. The method requires continued sampling of values of a large number of events by applying the mathematical theory of random variables. The SAC initial assessment used a Monte Carlo analysis to quantify uncertainty in the parameters selected.*

As will be demonstrated in the following sections, a relatively small number of input parameters determine most of the variability in the calculated performance measures. Interestingly, when the performance measure is human dose, variability with regard to individual behavior and exposure affects uncertainty in the estimated dose more than variability in inventory, release, or environmental transport of the contaminant. The same observation was made in the Hanford Environmental Dose Reconstruction Project (Farris at al. 1994, page 5.10).

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Uncertainty in the Human Risk/ Impact Model

Residential Farmer Using Groundwater Down Gradient of the 200 East Area. The residential farming scenario uses groundwater for irrigation of crops that are eaten by the farmer and livestock. In addition, the farmer indulges in recreational activities that include swimming and boating on the Columbia River. For this analysis, the location of the farm was considered to be just to the southeast of the 200 East Area. This location is near the centerline of the groundwater plume migrating toward the southeast toward the Columbia River. The performance measure is the radiation dose to the farmer from tritium. The model parameters contributing the most to the explanation of variability in the radiation dose at the year 2000 are provided in Table 11.1. Two of the realizations generated small tritium

Table 11.1. *Variability in the radiation dose to the residential farmer downgradient of the 200 East Area in 2000.*

Description	Additional R^{2} [(a)]
Internal dose factor for ingestion of tritium	.616
Ingestion rate of meat	.248
Release model outputs to the vadose zone transport model	.062
Transfer factor for tritium from animal food to animal tissue (meat)	.027

(a) R^2 is interpreted as the additional fraction of the variability that is explained as the associated variable is added to the regression model.

plumes and yielded low doses to the farmer. The other 23 realizations cover a span of 3 to 147 mrem per year at this location in 2000.

Exposure received during recreational activities is a minimal source of dose in this scenario. The largest source of variability (61.6%) in the dose estimate is due to the ingestion factor for tritium. As shown in Figure 11.1, the set of sampled ingestion dose factors for tritium cover a range where the largest value is about 20 times the smallest value. The variability in dose factors was selected using the approach of Snyder et al. (1994). An additional 24.8% of the variability in the dose is explained by the ingestion rate of locally grown meat (i.e., cattle on irrigated pasture). An additional 2.7% of the variability is explained by the transfer factor from cow food ingestion to cow tissue concentration by the meat animal. In this case, only about 6.2% of the variability is explained by a previous model, VADER, that calculates the release of contaminants into the vadose zone. The other 4% of the variability is explained by a combination of several other model parameters.

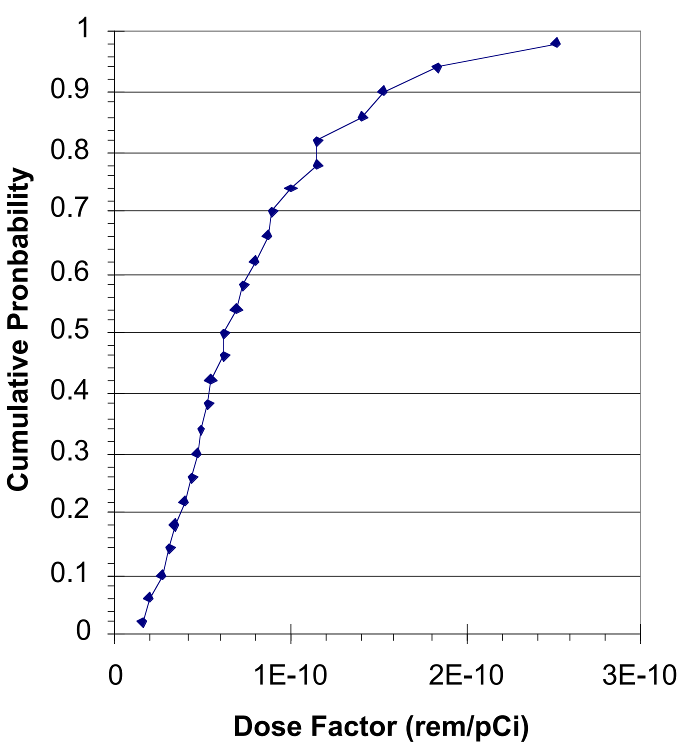

__Figure 11.1.__ Sampled set of tritium ingestion dose factors.

The results provided in Table 11.1 are applicable to the year 2000. At that time the total dose from all nuclides is dominated by the contribution from tritium. However, tritium decays faster than the other nuclides, so within about 40 years technetium-99 becomes the largest contributor to dose. The mean value of the contribution of individual nuclides to total dose as a function of time is shown in Table 11.2.

This uncertainty analysis was extended to additional time periods. The performance measure again was the total radiation dose to the residential farmer. This analysis used a different run of the HUMAN code that used a different sampling sequence of random variables than the run examining the dose from only tritium. The model parameters contributing the most to the explanation of variability for the total dose as a function of time are presented in Table 11.3.

Table 11.2. *Percent contribution of individual nuclides to total dose by year (mean value) down gradient of the 200 East Area.*

Year	Technetium-99	Tritium	Iodine-129[a]	Uranium-238
2000	3.94%	95.87%	0.00%	0.19%
2020	19.71%	79.66%	0.00%	0.63%
2040	55.02%	43.32%	0.00%	1.66%
2060	81.06%	15.35%	0.01%	3.59%
2080	91.41%	4.54%	0.01%	4.04%
2100	94.24%	1.57%	0.01%	4.18%
2120	95.17%	0.80%	0.01%	4.02%
2200	97.15%	0.03%	0.00%	2.82%
2300	96.54%	0.00%	0.00%	3.46%
3000	96.84%	0.00%	0.01%	3.16%

(a) The current model significantly underestimates the iodine-129 dose at this location in the sense that the modeled groundwater plume for iodine-129 is substantially smaller that the observed plume.

The computational tools to perform uncertainty analyses have been developed and demonstrated for a limited set of performance measures.

The results in Table 11.3 illustrate that the key variables to describe uncertainty change with time at the same location. Also, several of the parameters contributing the most to the variability in total radiation dose are internal to the HUMAN code rather than being the product of the inventory, release, or transport models.

Residential Farmer Using Groundwater North of Gable Mountain Gap.
The residential farming scenario also was evaluated for a location just to the north of the gap between Gable Butte and Gable Mountain. This location is near the centerline of the groundwater plume migrating toward the north through the gap on the way to the Columbia River. The performance measure again is total radiation dose to the farmer. The model parameters contributing the most to the explanation of variability at the year 2000 are provided in Table 11.4.

Although the overall quantities of radionuclides and chemicals generated on the Hanford Site are relatively well known, the actual amount in specific waste sites is uncertain.

Table 11.3. *Variables that contribute the most to the variability for the radiation dose to a residential farmer at different years.*

Year	Additional R^2 [(a)]	Description
2040	36.2	Concentration of technetium-99 in groundwater
	18.3	Ingestion rate for leafy vegetables
	9.4	Concentration ratio of technetium-99 in vegetation
	7.3	Transfer factor for tritium into meat animal
2100	22.9	Technetium-99 dose factor for ingestion
	15.8	Concentration of technetium-99 in groundwater
	11.1	Concentration ratio of technetium-99 in vegetation
	14.0	Ingestion rate for leafy vegetables
	7.0	Soil ingestion rate for an adult
2200	40.2	Technetium-99 dose factor for ingestion
	9.6	Ingestion rate for leafy vegetables
	8.4	Amount of water ingested by a meat animal
	7.1	Concentration ratio of technetium-99 in vegetation
2300	38.3	Technetium-99 dose factor for ingestion
	14.1	Ingestion rate for leafy vegetables
	11.4	Concentration of technetium-99 in groundwater
	6.6	Concentration ratio of technetium-99 in vegetation
2400	37.7	Technetium-99 dose factor for ingestion
	12.0	Ingestion rate for leafy vegetables
	11.1	Concentration of technetium-99 in groundwater
	6.7	Concentration ratio of technetium-99 in vegetation
3000	30.3	Technetium-99 dose factor for ingestion
	10.0	Concentration ratio of technetium-99 in vegetation
	8.7	Exposure time to contaminated soil
	8.4	Ingestion rate for leafy vegetables

(a) R^2 is interpreted as the additional fraction of the variability that is explained as the associated variable is added to the regression model.

Table 11.4. Variability in the residential farmer dose north of Gable Gap in 2000.

Description	Additional R^{2} (a)
Internal dose factor for ingestion of tritium	.527
Ingestion rate of meat	.247
Vadose zone model outputs to groundwater	.081
Water intake rate for a meat animal	.029

(a) R^2 is interpreted as the additional fraction of the variability that is explained as the associated variable is added to the regression model.

One of the challenges associated with performing an assessment is the appropriate presentation of how well the results predict what actually may occur.

In the year 2000, the modeled dose at this location also is dominated by the magnitude of the tritium plume in groundwater. The dose from tritium is about 89% of the total dose; the dose from technetium-99 is about 10% of the total dose, and uranium accounts for 1% of the total dose. The recreational activities are a minimal source of dose in this exposure scenario and do not contribute significantly to the variability in the dose. The largest source of variability (52.7%) in the dose estimate is due to uncertainty in the ingestion dose factor for tritium. The tritium ingestion dose factors for this scenario are the same ones shown in Figure 11.1. An additional 24.7% of the variability in the dose is explained by the ingestion rate of locally grown meat (cattle grazing on irrigated fields). An additional 2.9% of the variability is explained by the variation in the water intake rate by the meat animal. In this case, about 8.1% of the variability is explained by a previous model, STOMP-200E, that calculates the release of contaminants from the vadose zone into the groundwater in the 200 E Area. The other 5% of the variability is explained by a combination of several model parameters.

Native American Subsistence Lifestyle Scenario in the 300 Area. The variability of the total radioactive dose for the Native American Subsistence lifestyle scenario was evaluated at the 300 Area for the year 2000. In terms of the average dose, the nuclides contributed the following fractions to the total dose: uranium-238, .7330; technetium-99, .1822; tritium, .0775; strontium-90, .0017; and iodine-129, .0003. However, the uranium dose ranged from near zero to being the largest contributor to the total dose. Thus, as seen in Table 11.5, uranium-238-related variables have the most influence on the variability in total dose.

Uncertainty in the cultural risk/impact model is mostly due to uncertainty in the concentration of contaminants in groundwater plumes.

Two observations can be made from the results shown in Table 11.5. First, unlike the other human scenarios, the largest sources of variability for this exposure scenario are not parameters internal to the human exposure model. Second, parameters specific to tritium do not dominate the variability for this early time because tritium contributes only about 8% of the total dose at this location.

Table 11.5. *Variables contributing the most to the variability in the radioactive dose for the Native American subsistence scenario at the 300 Area.*

Description	**Additional $R^{2\ (a)}$**
Distribution coefficient (K_d) of uranium in river bottom sediment	.441
Release of uranium to the groundwater in the 300 Area	.148
Water intake rate for a bird that is eaten as food	.107
Retardation of uranium in the groundwater transport model	.029

(a) R^2 is interpreted as the additional fraction of the variability that is explained as the associated variable is added to the regression model.

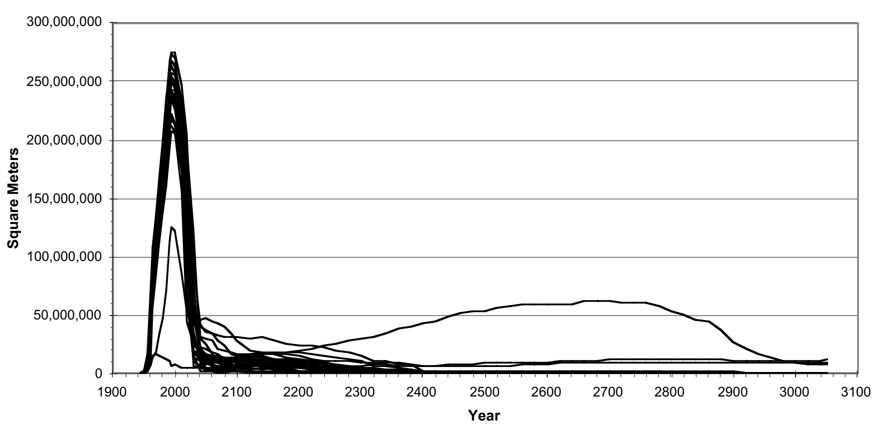

Figure 11.2. *Area where at least one contaminant exceeds the drinking water standard in groundwater.*

Uncertainty in the Cultural Risk/Impact Model

The size of the land area where the concentration of one or more contaminants in groundwater exceed their respective levels for drinking water in the drinking water standard is shown in Figure 11.2. The magnitude of the peak centered at about the year 2000 is largely driven by tritium, although uranium-238 and chromium also have sizeable groundwater plumes up until about the year 2300. The larger groundwater plumes after the year 2400 are due almost entirely to an iodine-129 plume from the State-Approved Land Disposal Site in about a quarter of the realizations. The presentation for the uncertainty analysis focuses on the size of the tritium groundwater plume, which is shown in Figure 11.3. For the year 2000, the tritium plume accounts for about 95% or more of the groundwater plume size for all contaminants.

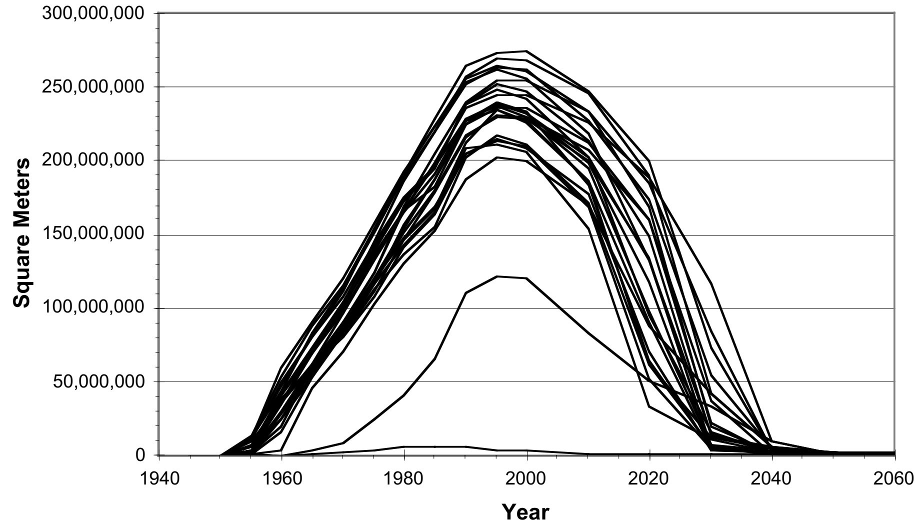

Figure 11.3. *Land area where the concentration of tritium in groundwater exceeds the drinking water standard (20,000 pCi/L).*

The only stochastic variable in the groundwater model is the sorption coefficient. Since this variable has a constant value of zero for tritium, the variability in the groundwater plume size is due entirely to the variability in the derived parameter of release of tritium to the groundwater. A plot of the tritium plume size versus the cumulative amount of tritium released to the groundwater at the year 2000 is provided in Figure 11.4.

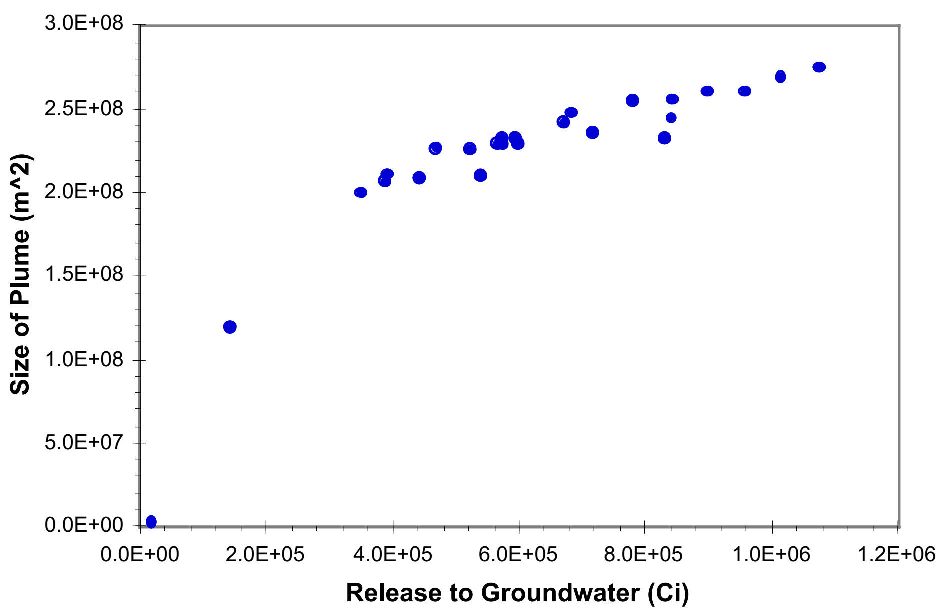

Figure 11.4. *Size of the groundwater plume where tritium concentrations are above 20,000 pCi/L versus cumulative releases of tritium to groundwater (Year 2000).*

A second-tier regression model was used to examine the source of the variability in the releases of tritium to groundwater. This model used the derived releases from the waste form model (VADER) and the stochastic variables internal to the vadose zone model (STOMP) in an attempt to explain the variability in release to groundwater. The parameters controlling the variability are described in Table 11.6.

In this case, in which the plume size is mostly due to liquid disposals of a non-sorbing radionuclide, no single parameter in the vadose zone model dominates the uncertainty in releases. However, the set of model parameters described in Table 11.6 accounts for about 87% of the variability in the releases to groundwater.

The major conclusion for this case is that the variability in the release of tritium to groundwater, and hence also the variability in the size of the groundwater plume, is due almost entirely to a series of hydrologic parameters in the vadose zone model. Thus, for liquid releases with contaminants that are not retarded, the variability in the release to the saturated zone is not dependent on the variability in the inventory. However, the tritium flux to the water table does drive the magnitude of the groundwater plume size.

Table 11.6. *Parameters controlling variability in the release to groundwater in 2000.*

Description	**Additional R^2 (a)**	**Notes**
Porosity Hss (Hanford silty sand)	.183	Most porous vadose zone layer, as a distribution
Hydraulic conductivity PPlz (Early Palouse) soil	.152	Most confining vadose zone layer, as a distribution
Van Genuchten *n* parameter Rg (Ringold) (hydraulic conductivity in unsaturated soil)	.135	Lowest values of *n*, as a distribution
Residual saturation Hcs (Hanford coarse sand)	.104	Moderate residual saturations, as a distribution
Residual saturation PPlc (Plio-Pliestocene caliche)	.088	Highest residual saturation, as a distribution
Porosity PPlz (Early Palouse) soil	.084	Second-highest porosity, as a distribution
Porosity Hfs (Hanford fine sand)	.070	Moderately high porosity, as a distribution
Porosity Rg (Ringold)	.058	Lowest porosity, as a distribution

(a) R^2 is interpreted as the additional fraction of the variability that is explained as the associated variable is added to the regression model.

A similar analysis was performed to examine the sources of variability for the size of the technetium-99 groundwater plume. The regression model indicates that about 78% of the variability in the plume size is explained by the release of technetium-99 to groundwater in the 200 East Area. No other single parameter contributed any significant amount to the variability. The relationship between release of technetium-99 from the vadose zone in the 200 East Area and the groundwater plume size is shown in Figure 11.5. The retardation value for technetium-99 in the groundwater model was stochastic, but it was not a significant source of variability relative to plume size.

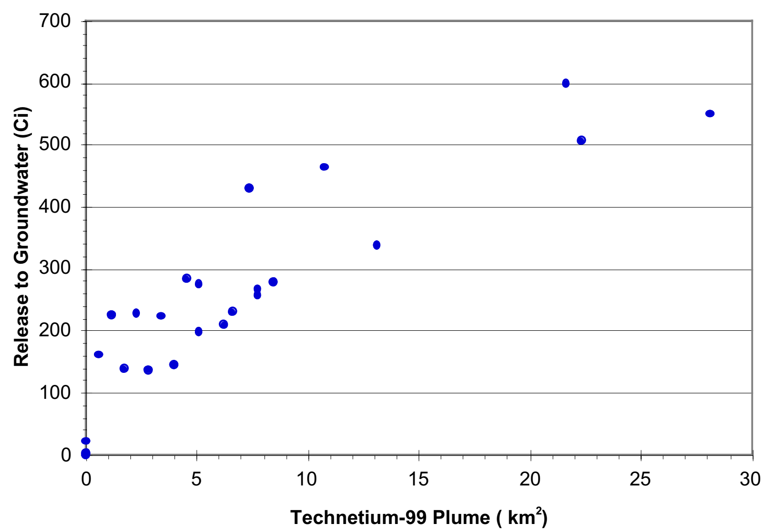

Figure 11.5. *Comparison of the release of technetium-99 to groundwater in the 200 East Area to the size of the groundwater plume with concentration above the drinking water standard (Year 2000).*

Uncertainty in River Water Concentrations

The concentration of tritium in surface water in the Columbia River is described in Chapter 7. The sources of uncertainty were examined using the suite of uncertain parameters in the river model and the derived set of releases to the groundwater model. In this case, the releases to the groundwater model were divided into two cases: the releases to the groundwater in the 200 East Area and the releases to groundwater for the rest of the site. The regression model results are provided in Table 11.7 for the year 2000, using the estimated water concentrations at the Richland Pumphouse.

Uncertainty about the concentration of tritium in Columbia River water is mainly due to the variability in the amount of tritium released in the 200 East Area.

The derived parameter explaining the largest source of variability (81.1%) is the release of tritium to the groundwater from the vadose zone in the 200 East Area. This derived parameter was used because there are no stochastic parameters in the groundwater transport model for tritium. An additional 4.1% of the variability is due to the background concentrations in the river as it enters the upstream edge of the river transport model. A small additional amount (2.6%) of variability is explained by tritium releases to the groundwater for all release sites outside the 200 East Area. No other parameter contributed significantly to the variability in tritium concentrations.

Table 11.7. Parameters effecting the variability of tritium concentrations in the Columbia River at the Richland Pumphouse in 2000.

Description	Additional R^{2} [(a)]
Vadose zone model outputs to groundwater in the 200 East Area	.811
Background concentration of tritium in river water at Priest Rapids Dam	.041
Vadose zone model outputs to groundwater for the Hanford site, excluding the 200 East Area	.026

(a) R^2 is interpreted as the additional fraction of the variability that is explained as the associated variable is added to the regression model.

Uncertainty in the Ecological Model

Juvenile Salmon (Aquatic Species) Exposed to Chromium. An uncertainty analysis was performed for the ecological model in the 100 K Area to determine the impact from chromium to a juvenile salmon in the year 2000. In this one area of the river the environmental hazard quotient (body burden normalized by a no observed adverse effects level) for the juvenile salmon is below 1, thus no adverse effects are expected. Application of a regression model showed that 92.8% of the variability of the environmental hazard quotient is explained by the variability of the body burden of the mayfly. The relationship between the environmental hazard quotient for the juvenile salmon and the body burden of the mayfly is shown in Figure 11.6. This result is not unexpected because about 95% of the food intake by the juvenile salmon comes from consumption of mayfly.

A second-tier regression model was used to determine the sources of variability in the body burden for the mayfly. About 98.2% of the variability in the body burden of the mayfly was explained by the concentration of chromium in periphyton. Another 1% of the variability was explained in the variability of the mayfly depuration rate. A third-tier regression model indicates that 99.5% of the variability in the periphyton body burden is explained by the variation in the chromium concentrations in river bottom pore water.

Beaver (Terrestrial Species) Exposed to Radioactive Contaminants. Another uncertainty analysis was performed for a beaver in the year 2000 exposed to radioactive contaminants at the same location (100 K Area) as the Columbia Pebble Snail. Tritium accounted for about 99.9% of the average dose of 1.5×10^{-6} rad/day. The first tier of the analysis showed that 99.9% of the variability in the dose to the beaver was accounted for by the variability in the concentration of tritium in the black cottonwood and mulberry trees that make up its diet.

A second tier uncertainty analysis showed that 91.7% of the variability of the tritium concentration in black cottonwood and mulberry trees could be explained by variation in the seep water concentration where the tree grows. None of the other variables in the exposure model for the black cottonwood explained any significant amount of the variability.

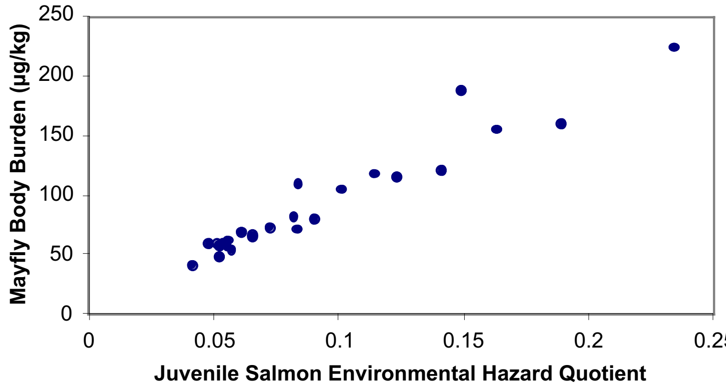

Figure 11.6. *Relationship between the chromium environmental hazard quotient for a juvenile salmon and the body burden for a mayfly at the 100 K Area (Year 2000).*

A third tier analysis could have explored the sources of variability in the concentration of tritium in seep water. The model for seep water is essentially the average of the groundwater concentration and the surface water concentration. This avenue was not explored further because of the uncertainty analyses considered for tritium in groundwater earlier in this section.

This chapter provides a number of uncertainty analysis results and identifies some of the parameters that control uncertainty for specific performance measures. Different performance measures, exposure scenarios, and locations of interest lead to identification of a wide range of key variables for explaining uncertainty. These key variables provide insight to help guide future investigations to obtain data or update models to help reduce the overall output variability. Given the number of performance measures and exposure scenarios of interest, it is not possible at this time to narrow the overall treatment of uncertainty to few parameters or models.

A major purpose of the initial assessment was to demonstrate the capability to conduct a sitewide assessment while providing uncertainty estimates for a wide group of performance measures. The computational tools to perform these analyses have been developed and demonstrated. They are sufficiently advanced to support narrowing the list of key contaminants, key waste sites, and key uncertain parameters, provided that specific performance measures are chosen for specific locations.